

#### Stream temperature and flow predictions

#### help answer key questions

Is the water cold enough?





Is the water warm enough?

Will we have enough to drink?





Will the river flood?

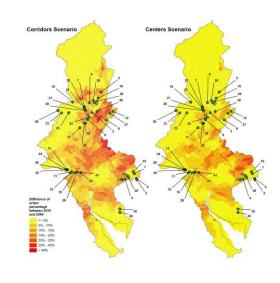


# Stream temperature and flow predictions inform key decisions

How much water should we release today to meet stakeholders' short-term and long-term needs?

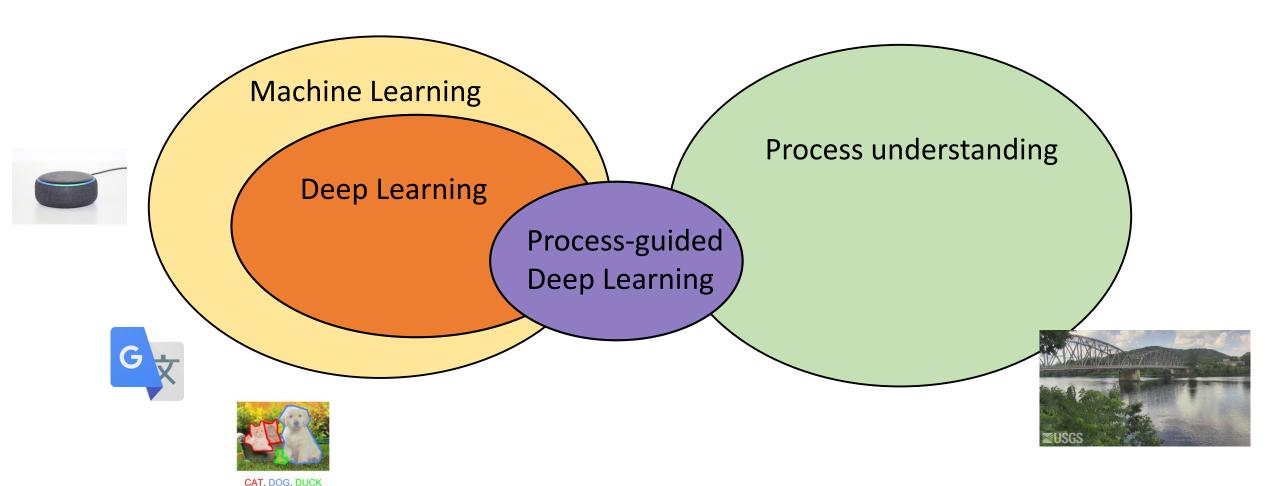


What long-term policies can we focus on now given anticipated climate and land use change?





## Process-guided Deep Learning





## How do we incorporate process-understanding?

#### 1. Time aware modeling

ML

**PGDL** 

(yesterday affects today)

#### 2. Energy budget constraint

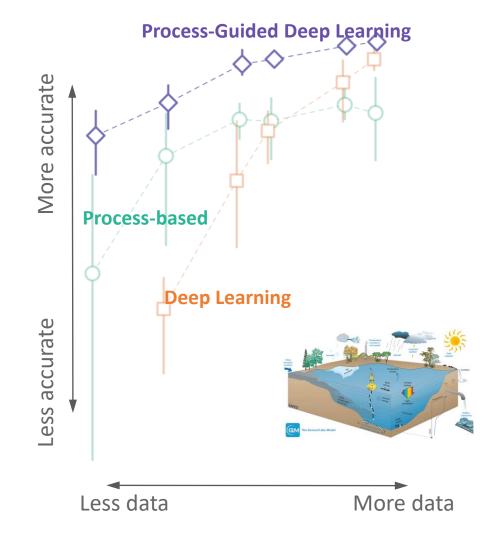
(penalty for physically impossible predictions)

## 3. Pretraining with a process-based model

(physically consistent starting point)

#### 4. Space aware modeling (for streams)

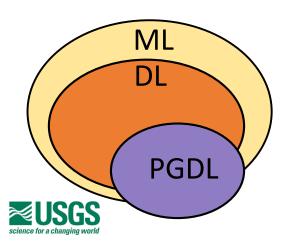
(upstream affects downstream)





#### How do we incorporate process-understanding?

- 1. Time aware modeling
- 2. Energy budget constraint
- 3. Pretraining with a process-based model
- 4. Space aware modeling (for streams)
- 5. Multi-task modeling of related variables



## multi-task deep learning



Primary objective: learn to read (unseen books)





### multi-task deep learning

Primary objective: learn to read (unseen books)





Read the words



VS



#### Multi-task

Read the words



Describe the picture





#### multi-task deep learning

Primary objective: predict streamflow (in unseen conditions)

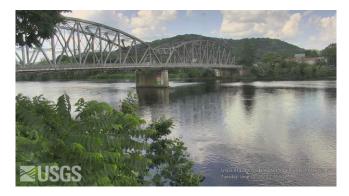


Single-task

Predict streamflow



VS



Multi-task

Predict streamflow



Predict temperature

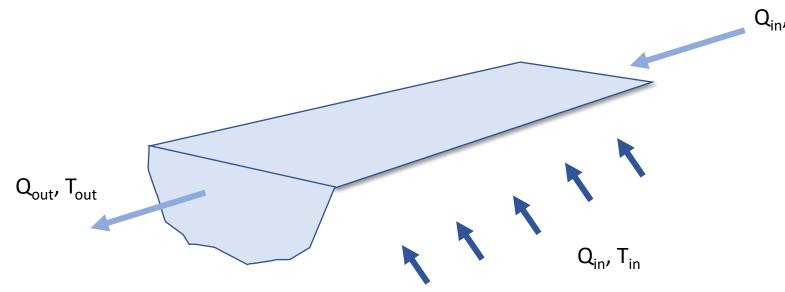




### Why Streamflow and Stream temperature

Both part of the energy transfer process

Incoming water flowing from surface runoff or groundwater brings energy into a stream segment. This affects changes in streamflow and stream temperature.





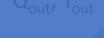


## Why Streamflow and Stream temperature

Intuition: If a model/learns from two aspects of the energy transfer process (streamflow and water temperature), Incoming water flowing from surface runoff or groundwater brings energy

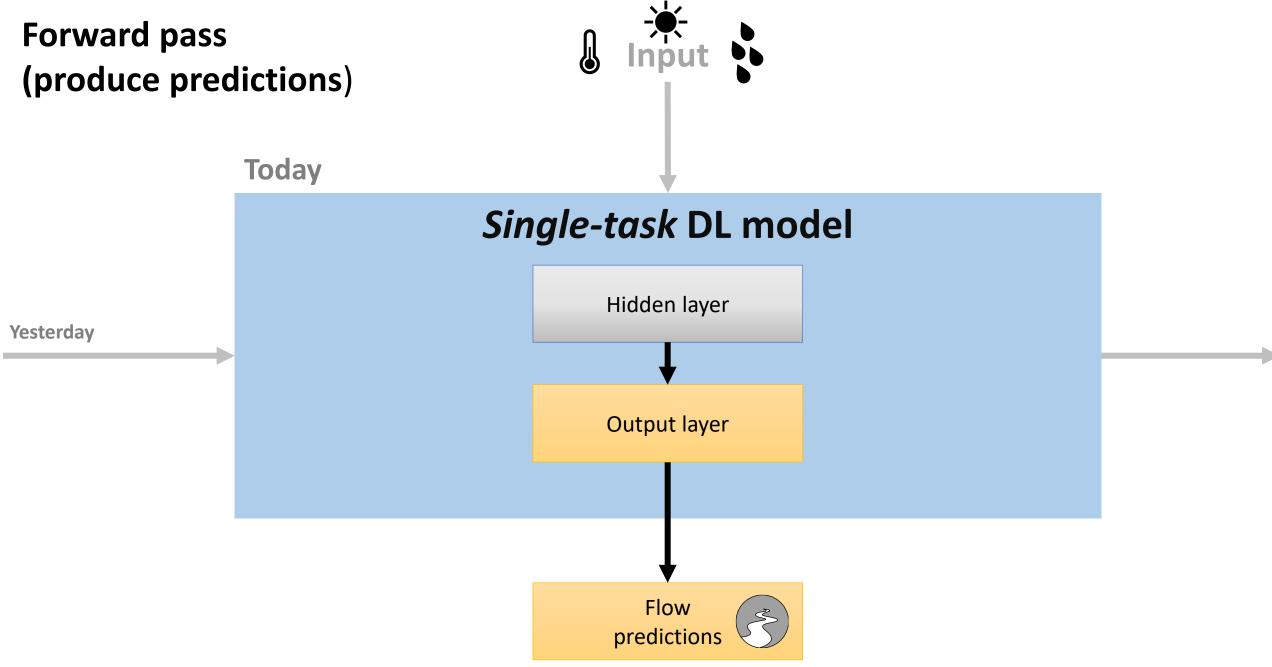
then, it should learn to model the universal process better

and will therefore be able to make better predictions with unseen input

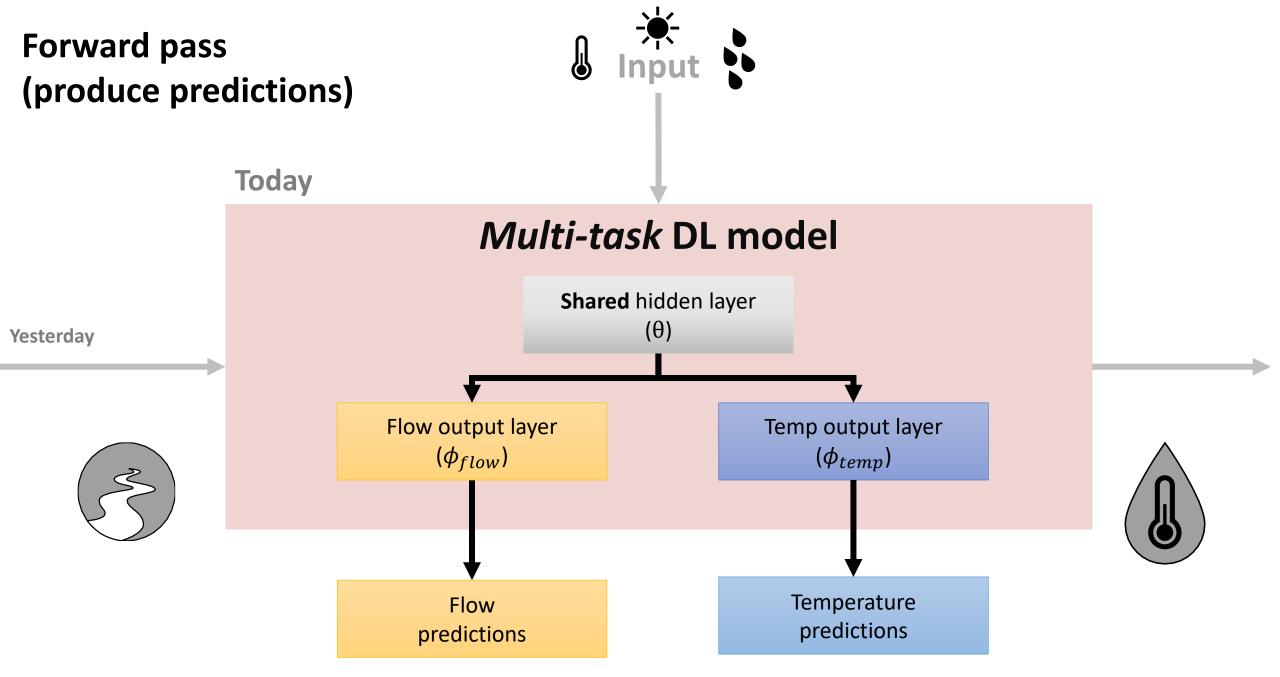








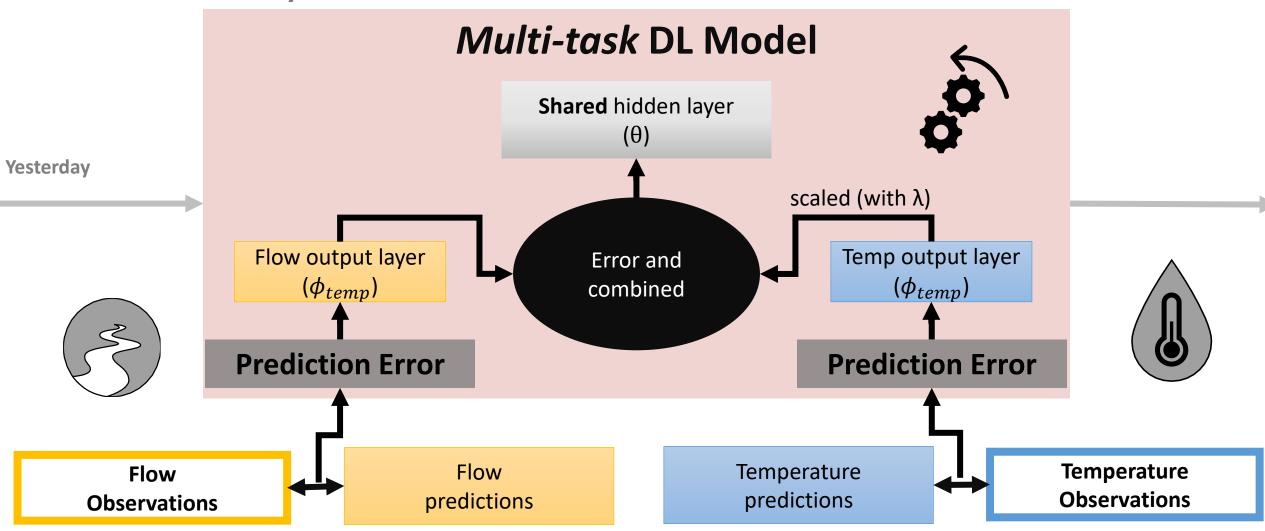




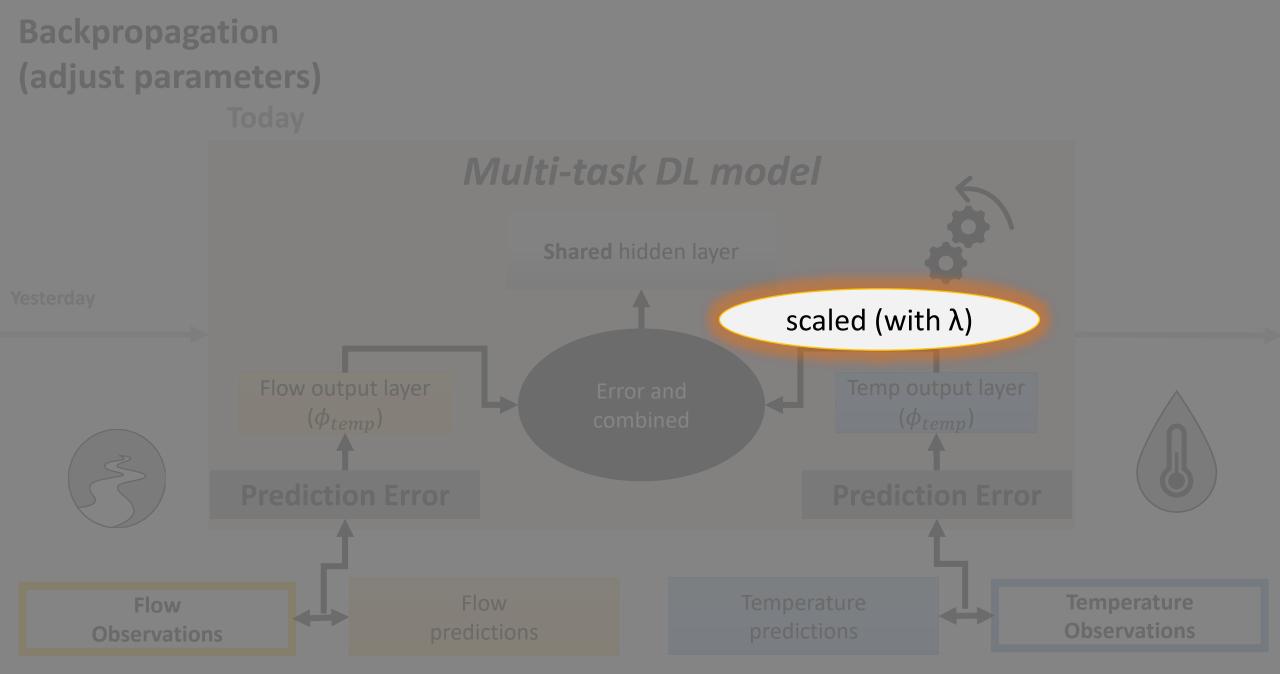


## Backpropagation (adjust parameters)

Today









# Gradient descent: updating the shared hidden layer parameters ( $\theta$ )

$$\theta(i+1) \coloneqq \theta(i) - \alpha \left[ \nabla_{\theta} \mathcal{L}_{flow}(\theta(i), \phi_{flow}(i)) + \lambda \nabla_{\theta} \mathcal{L}_{temp}(\theta(i), \phi_{temp}(i)) \right]$$

Gradient from errors in flow predictions

Gradient from errors in temp predictions



## Gradient descent: updating the shared hidden layer parameters $(\theta)$

$$\theta(i+1) \coloneqq \theta(i) - \alpha \left[ \nabla_{\theta} \mathcal{L}_{flow}(\theta(i), \phi_{flow}(i)) + \lambda \right]_{\theta} \mathcal{L}_{temp}(\theta(i), \phi_{temp}(i))$$

Gradient from errors in flow predictions

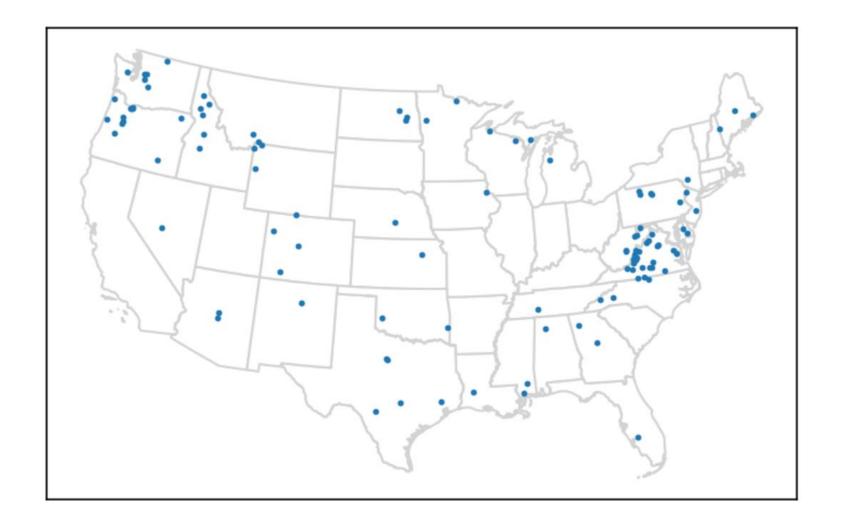
Multi-task scaling factor Gradient from errors in temp predictions



#### Experiments

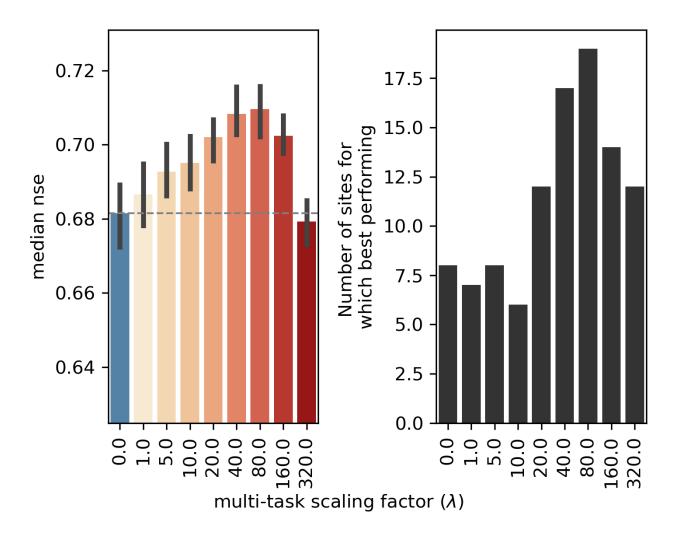
103 sites across the US

Part of CAMELS dataset (preprocessed flow/weather/attribute data)



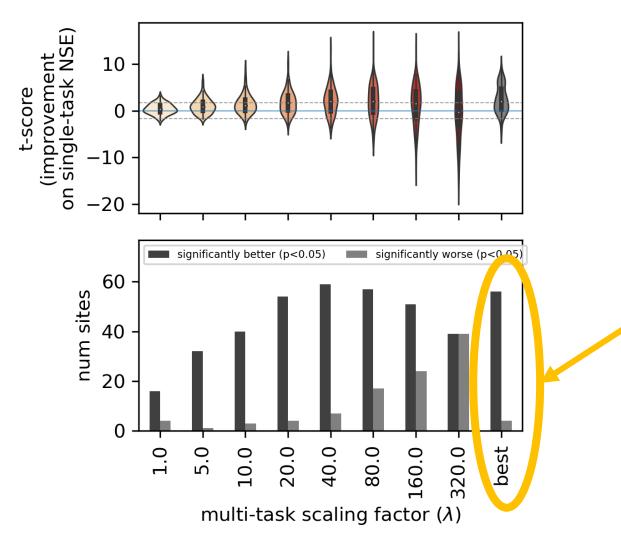


#### Results: Effect of multi-task scaling factor





#### Results: Effect of multi-task scaling factor

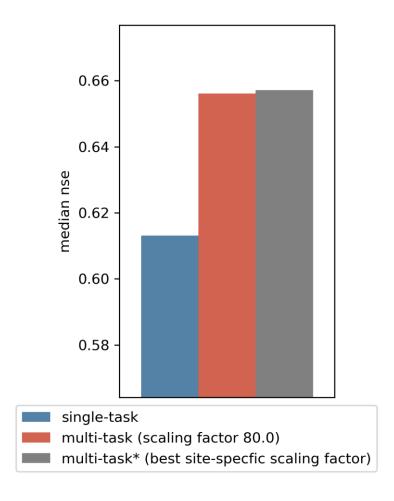


When the multi-task scaling factor was tuned on a siteby site basis:

- majority of sites significantly improved
- very few sites were significantly worse

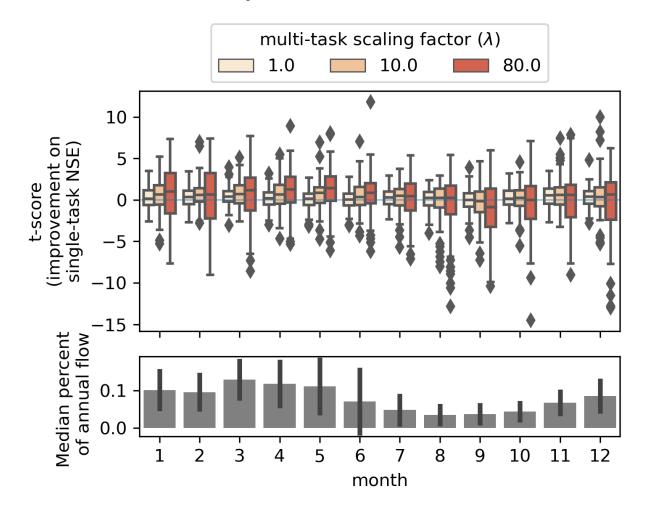


#### Results: Multi-task is overall more accurate





#### Results: Seasonality

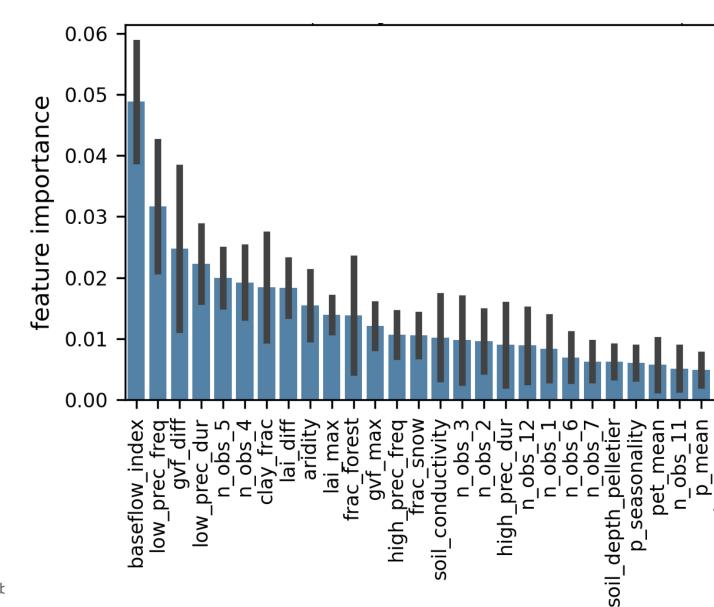




#### Results: Seasonality

- Feature importances for predicting t-scores of multi-task model with scaling factor of 80
- R2 = 0.27

 Baseflow index was by far the most important variable





# Stream temperature and flow predictions inform key decisions

- ~28k either streamflow or water temperature
- 19% flow **and** temp\*
- 78% only flow

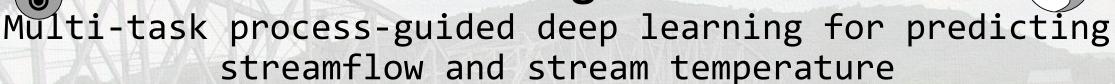
\*Measuring temperature continuously costs less than 1/6 of measuring discharge

If properly configured, multi-task models could be an effective way to leverage these data to improve streamflow predictions





#### Better Together?



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This information is preliminary and is subject to revision. It is being provided to meet the need for timely best science. The information is provided on the condition that neither the U.S. Geological Survey nor the U.S. Government shall be held liable for any damages resulting from the authorized or unauthorized use of the information.